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Comparative evaluation of global low-carbon urban transport

Wenxiang Li[a], Lei Bao[b,*], Luqi Wang[c], Ye Li[a,*], Xianmin Mai[e]

[a] The Key Laboratory of Road and Traffic Engineering, Ministry of Education, College of Transportation Engineering, Tongji University, 4800 Cao' an Road, Shanghai 201804, PR China
[b] Seazen Holdings Co., Ltd., No.6 Lane 388, Zhongjiang Road, Putuo District, Shanghai 200062, PR China
[c] School of Management, Harbin Institute of Technology, No. 92, Xidazhi Street, Harbin 150000, PR China
[e] School of Urban Planning and Architecture, Southwest Minzu University, 16 South Section, 1st Ring Road, Chengdu, Sichuan, 610041, PR China

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ABSTRACT

Given increasing concern about climate change, the trend toward low-carbon urban transport development has global appeal. The evaluation of low-carbon urban transport is a prerequisite for a transition toward low-carbon urban transport. However, most of the existing research focuses only on the absolute evaluation of urban transport CO_2 emissions, which do not represent the level of low-carbon urban transport. In addition, an absolute evaluation is not comparable across different cities over time because it ignores the effects of urban heterogeneity. Therefore, this paper develops a comparative evaluation method that considers the effects of urban population scale, population density and economic development. A benchmark model of per capita CO_2 emissions for different cities with different properties is established based on the relationships between urban population scale, population density, and economic development. Then, a comparative evaluation index is derived from the benchmark model to independently evaluate the effects of policy factors, which may reflect the level of low-carbon urban transport. As a result, cities with low-carbon urban transport can be identified. Furthermore, four urban transport transition types are identified: stable high-carbon transitions, stable low-carbon transitions, low-carbon transitions, and high-carbon transitions. These methods are applied to 180 cities worldwide to verify their effectiveness. This is the first time that 180 global cities have been compared using a unified and quantitative evaluation index of low-carbon urban transport.

1. Introduction

Currently, cities around the world accommodate more than half of the world's population, consume over 85% of its resources and energy and emit 75% of the total greenhouse gases (Bulkeley, 2013). The consumption and emissions of cities are far beyond the limits of sustainability. Therefore, it is imperative to develop low-carbon cities (Su et al., 2012). Since the transport sector produced 24% of CO_2 emissions of energy use in 2015 (Birol, 2017), urban transport should be the focus of low-carbon development, and the evaluation of low-carbon urban transport is thus a prerequisite for the transition toward low-carbon urban transport.

Low-carbon urban transport is usually characterized by effective strategies and instruments (Nakamura and Hayashi, 2013) that keep the CO_2 emissions of urban transport at a relatively low level, such as carbon taxes, CO_2 emission trading, or subsides for cleaner vehicles (Li et al., 2016). In this case, the main question is how to quantify the level of low-carbon urban transport. This question is more complex than the absolute measurement of urban transport CO_2 emissions because the definition and criteria for low-carbon urban transport are inconsistent and vary over time and by city. In addition, the heterogeneity of the populations and the economies of different cities around the world may also result in incomparable evaluation results. Therefore, it is arbitrary to determine whether urban transport is low-carbon simply based on the total or the per capita urban transport CO_2 emissions of a city.

For example, in 2012, the per capita transport emissions were 0.38 ton/person in Shanghai and 0.37 ton/person in Tokyo. Can we thus conclude that Shanghai and Tokyo have the same level of low-carbon urban transport because the per capita CO_2 emissions in these two cities are similar? The answer is absolutely not because Tokyo is famous for being a low-carbon city, while the CO_2 emissions of Shanghai have rapidly increased in recent years (Luo et al., 2017a). Indeed, the population scale, population density, and per capita gross domestic product (GDP) were significantly different for these two cities in 2012: the total population was 23.8 million in Shanghai and 13.2 million in Tokyo; the population density was 3.7 thousand per square

* Corresponding authors.
E-mail addresses: lwxffff@gmail.com (W. Li), baolei1225@gmail.com (L. Bao), luqiwang@hit.edu.cn (L. Wang), jamesli@tongji.edu.cn (Y. Li).

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kilometer in Shanghai and 9.5 thousand per square kilometer in Tokyo; and the per capita GDP was 13,471 USD in Shanghai and 45,277 USD in Tokyo. These figures indicate that Tokyo is a mature megacity that has experienced rapid development, while Shanghai is a rapidly developing megacity. Therefore, the effects of policy measures for low-carbon urban transport in these two cities are not comparable. This case illustrates the inability of an absolute measurement of CO_2 emissions to evaluate the level of low-carbon urban transport.

Regardless, to the best of our knowledge, most of the existing related studies have focused on the absolute evaluation of urban transport emissions (Geels, 2012; Khanna et al., 2014). The absolute evaluation neglects the influence of urban population and economic development on urban transport CO_2 emissions. In addition, there are few quantitative criteria for identifying low-carbon urban transport. None of the previous studies have evaluated and compared the level of low-carbon urban transport across different global cities considering the heterogeneity of their populations and economies. Thus, it is difficult for cities to determine their own relative positions globally, making it difficult to carry out appropriate policy measures and potentially impeding the development of low-carbon urban transport.

To address the above problems, this study aims to establish a comparative evaluation method that can offer a uniform comparison of low-carbon urban transport across different global cities. A benchmark model of the per capita CO_2 emissions of urban transport in 180 global cities with different properties is established based on the relationships between the urban population scale, population density, and economic development. Then, a comparative evaluation index is proposed to measure the level of low-carbon urban transport based on the benchmark value of per capita CO_2 emissions. In this case, the 180 global cities are compared and ranked based on the comparative evaluation index. Finally, we identify the level of low-carbon urban transport and the low-carbon transition of the 180 global cities using a unified criterion.

The contribution of this study is that it proposes a novel and effective method for evaluating the level of low-carbon transport in different global cities with heterogeneous populations and economies. This is the first time that 180 global cities have been compared using a unified and quantitative evaluation index for low-carbon urban transport. This evaluation index is based on the benchmark value of the per capita CO_2 emissions of urban transport rather than upon the absolute value, which increases comparability and accuracy. As a result, the evaluation results are all comparable, allowing for horizontal and vertical comparisons of the urban transport in different cities and during different periods. Furthermore, this study can help cities identify their stage of low-carbon urban transport development and learn from the successful experiences of benchmark cities.

The remaining sections of this paper are organized as follows. The next section is a literature review. Section 3 presents the data used in this study and some preliminary analyses. The effect analyses and comparative evaluation method are described in Section 4. Section 5 presents the results and further discussion. The final section summarizes the main findings, policy implications, and future research directions of this study.

2. Literature review

2.1. Measurement of urban transport CO_2 emissions

The most popular methods for measuring transport CO_2 emissions are divided into two categories: top-down and bottom-up approaches (van Vuuren et al., 2009). The former is derived from the total consumption of transport fuels multiplied by CO_2 emission factors, while the latter is based on the sum of individual energy-related activities. Due to the mobility of vehicles and the boundaries of cities, the bottom-up approach is more suitable for measuring urban transport (Schipper et al., 2009). In particular, it provides more information about the factor effects for policymakers. However, it also depends more on detailed and accurate data collection. For example, Wang et al. (2007) used data from the vehicle population, the annual vehicle kilometers traveled and fuel efficiency to calculate CO_2 emissions from the road transport sector in China. In addition, some models, such as MOVES, COPERT, HBEFA, and IVE, were developed with local emission inventories to estimate transport emissions (Bongardt et al., 2013). Apart from studies on the direct emissions of vehicles, there has also been some research conducted analyzing the life cycle of transport emissions, which includes the emissions from infrastructure construction, energy production (tank-to-wheels and well-to-tank) and vehicle manufacturing, maintenance and disposal (Brand et al., 2012; Li et al., 2018b). Furthermore, emerging information communication technologies enable the in-depth study of transport emissions. For example, Luo et al. (2017b) applied big data analysis to GPS data from taxies to explore the spatial-temporal features of taxi emissions in Shanghai, China.

However, all the measurements above only represent the absolute quantity of transport CO_2 emissions rather than the level of low-carbon development. An appropriate evaluation of low-carbon urban transport should include the comprehensive consideration of CO_2 emission measurement, the population, the economy and policy factors. Therefore, the measurement of CO_2 emissions provides the basis for the evaluation of low-carbon urban transport.

2.2. Evaluation of low-carbon urban transport

The existing research related to low-carbon evaluations has mainly focused on evaluating low-carbon decoupling and low-carbon evaluation index systems. Decoupling theory was developed by the Organization for Economic Cooperation and Development (OECD) at the beginning of this century and has expanded from agricultural policy research to economic environment research (Antón, 2006; Simonis, 2013; von Weizsäcker et al., 2014). The decoupling of CO_2 emissions refers to the weakening or even the disappearance of the correlation between economic growth and greenhouse gas emissions. Four main themes related to low-carbon decoupling have been discussed widely, including long-run emissions-output elasticities, changes in elasticity, consumption-based emissions and cyclical relationships (Cohen et al., 2018). Economic growth elasticity is used to show the decoupling of CO_2 emissions and has been an effective tool for measuring the low-carbon development level (Poumanyvong and Kaneko, 2010). For example, Tapio (2005) proposed the elasticity formula for the CO_2 emissions of road transport and evaluated the low-carbon level of the EU-15 from 1970 to 2001. Overall, a decoupling evaluation is mainly used to analyze the relationship between the economy and CO_2 emissions in different periods, while it is difficult to use to evaluate the low-carbon development of different cities in a specific time period. Thus, this method is not applicable to uniformly comparing low-carbon urban transport across different cities.

The low-carbon evaluation index system was first used to evaluate the low-carbon economy of a region. Then, some organizations developed index systems for measuring the relationship between transport development and the environment. For example, the European Union proposed the Transport and Environment Reporting Mechanism (TERM) for evaluating the progress and performance of policies integrating transport and the environment (Christy and Adjo, 2005). The Institute for Environment and Sustainability analyzed 10 index systems in different countries and proposed an evaluation index system for traffic activity sustainability that included economic, social, environmental, technological and political dimensions (Dobranskyte-Niskota et al., 2007). Aside from national-level systems, some evaluation index systems for cities have been proposed (Wang et al., 2018; Yang et al., 2011; Zhou et al., 2012). For example, in 2010, the Indian government developed a city-level evaluation index system for low-carbon urban transport development that includes five dimensions: mobility and accessibility, infrastructure and land use, safety and security,

Table 1
Data from global cities.

Datasets		ISADC	MCDST	MCD	MCD2015
Year		1960, 1970, 1980, and 1990	1995/1996	2001	2012
Number of cities		46	100	51	63
Number of indicators		80	230	120	85
Indicators	Population and economy	√	√	√	√
	Jobs	√	√	√	√
	Road networks	√	√	√	√
	Parking spaces	√	√	√	√
	Vehicle population	√	√	√	√
	Travel of inhabitants	√	√	√	√
	Public transportation	√	√	√	√
	Vehicle miles	√	√	√	
	Transport energy use	√	√	√	
	Transport emission		√		
	Infrastructure investment		√		

environmental impact and the economy (Tiwari and Jain, 2013). The key to evaluation index systems lies in determining the index weights. The common methods for calculating the weights include the Delphi method, principal component analysis, factor analysis and the analytic hierarchy process (Haapio and Viitaniemi, 2008). However, these also have evident disadvantages, such as subjectivity, instability, fuzziness and the high demand for data collection. More importantly, the evaluation index system neglects the heterogeneity of urban characteristics, such as population density, size and economic development, which may have significant effects on the evaluation. As a result, the evaluation results for cities with different urban characteristics are still not comparable.

2.3. Comparison of low-carbon cities

Low-carbon development at the city level has become increasingly popular in China and globally (Su et al., 2012), and scholars have begun to pay more attention to the evaluation and comparison of low-carbon cities (Cai et al., 2017). For example, Khanna et al. (2014) compared the action plans of 8 Chinese pilot low-carbon cities, which included the target, scope, and supporting measures. They found that many of the current low-carbon city plans under the National Development and Reform Commission (NDRC) program have a very broad scope and may not necessarily address key concepts related to carbon mitigation (e.g., energy efficiency). Su et al. (2016) reviewed the low-carbon practices of 36 Chinese cities, including the initialization of urban low-carbon development planning and the establishment of low-carbon demonstration areas, focusing on specific fields such as sustainable energy systems, ecological industry, green transportation, and green building. However, those studies are mainly qualitative analyses rather than quantitative comparisons. Therefore, it is difficult to determine whether a city is low-carbon.

Recently, Azizalrahman and Hasyimi (2018a, b) proposed a generic multicriteria evaluation model for independently measuring city performance and identifying whether a city is low carbon. The model's criteria include energy, water, land use, air quality and mobility. Ten pilot cities were compared using the model, and five cities were classified as low carbon, namely, Vancouver, Stockholm, São Paulo, Sydney, and London. The results were validated by comparisons with a previous study (Tan et al., 2017) that used entropy weight and a set of widely used criteria dealing with the economy, transport and energy in the ten selected cities. However, the method of multicriteria evaluation is more dependent on subjective judgment than objective evaluation, as the criteria and weights are predetermined by the researchers. Therefore, the results may be inconsistent depending on the weights of the criteria.

Although many researchers have proposed an evaluation model for low-carbon cities, to date there have been very few studies offering comparative evaluation of low-carbon urban transport. The exception is Mittal et al. (2016), who assessed comparable urban transport scenarios for China and India through 2050 using the AIM/End-use model with a detailed characterization of technologies. The business-as-usual scenario and the low-carbon scenario were analyzed to explore the future implications of the technological and infrastructural transformations that are likely to occur in the urban transport sector in these two countries. The results showed that India can learn from China and avoid urban transport lock-ins to gain cobenefits. Nevertheless, Mittal et al. (2016) only focused on the national-level assessment of the future instead of a city-level comparative evaluation of low-carbon urban transport. To better identify the successful experiences and practices of low-carbon urban transport, a global comparison of low-carbon cities is necessary.

3. Preliminary analysis

3.1. Data sources

To collect as much data as possible on global cities, multiple data sources are used in this study, including "An International Sourcebook of Automobile Dependence in Cities 1960–1990 (ISADC) (Kenworthy et al., 1999)", "UITP Millennium Cities Database for Sustainable Transport (MCDST) (Kenworthy and Laube, 2001)", "Mobility in Cities (MCD)" and "Mobility in Cities Database 2015 (MCD2015) (UITP, 2015)". These datasets contain up to 230 indicators for over 100 major cities in North America, Australia, Europe and other regions (excluding China). These indicators are categorized into urban transportation data, land use data, economic data, and environmental data; some of the data related to this study are presented in Table 1.

Since data from Chinese cities are not available in the above datasets, we collected and integrated the same type of indicators for 75 Chinese cities through multiple local surveys and statistics reports in China, including the China Statistical Yearbook, the China Construction Statistical Yearbook, a transport development annual report, and a household travel survey of local cities. The data availability from the different cities is presented in Table 2.

In total, data related to 180 cities in 44 countries on 6 continents were collected, including 94 Asian cities, 49 European cities, 21 North American cities, 7 Australian cities, 6 African cities, and 3 South American cities, as shown in Fig. 1. The full list of 180 cities is presented in Table A. 1. It should be noted that the time range of the data may vary from city to city. In other words, data are not available for some cities in some years.

3.2. Measurement of the urban transport CO_2 emissions

Urban transport includes all the transport modes used by the

Table 2
Data from Chinese cities.

Cities		Beijing	Shanghai	Shenzhen	Other cities
Year		1986, 2000, 2005, 2010, and 2014	1986, 1995, 2004, 2009, and 2014	1998, 2005, and 2010	2010
Indicators	Population and economy	√	√	√	√
	Jobs				
	Road networks		√	√	
	Parking spaces		√		
	Vehicle population	√	√	√	√
	Travel of inhabitants	√	√	√	√
	Public transportation	√	√	√	
	Vehicle miles	√	√	√	
	Transport energy use		√		
	Transport emission		√		
	Infrastructure investment	√	√	√	

inhabitants of a city, excluding intercity transport and freight transport. It can be further divided into three types: high-carbon modes (passenger car, taxi, and motorcycle), low-carbon modes (bus, subway, and ferry) and zero-carbon modes (walking and bicycle). Therefore, only the CO_2 emissions of the high-carbon and low-carbon modes of urban transport needed to be measured.

Both top-down and bottom-up approaches were applied to measure the CO_2 emissions of urban transport in different cities based on data availability. The CO_2 emissions of cities with energy consumption data were measured using the top-bottom method. For cities without energy consumption data, the bottom-top method was used to calculate transport emissions.

The top-down measurement formula is presented as follows:

$$C = \sum_i F_i \times E_i \tag{1}$$

where C is the CO_2 emissions of urban transport, i is the fuel type, F_i is the consumption of fuel type i, and E_i is the CO_2 emission factor of type i.

The bottom-up measurement formula is presented as follows:

$$C = \sum_i \sum_j N_{ij} \times M_{ij} \times AF_{ij} \times E_i \tag{2}$$

where j is the vehicle type, N_{ij} is the number of vehicles j using fuel i, M_{ij} is the average annual mileage of vehicle j using fuel i, and AF_{ij} is the average annual fuel consumption of vehicle j using fuel i.

The per capita CO_2 emissions is calculated as follows:

$$PC = C/P \tag{3}$$

where PC is the per capita CO_2 emissions of urban transport, and P is the urban population scale.

3.3. Absolute evaluation analysis

The urban transport CO_2 emissions of 180 cities is estimated using the above data and measurement method. Then, we ranked the cities based on the absolute measure of CO_2 emissions of urban transport in 2012, as shown in Fig. 2, where Fig. 2(a) presents the ranking distribution of the 75 Chinese cities and Fig. 2(a) presents the ranking distribution of all 180 global cities. In addition, 4 Chinese megacities, Beijing, Shanghai, Guangzhou, and Shenzhen, are highlighted in Fig. 2. In this case, we can determine the positions of the Chinese and global cities. In terms of total CO_2 emissions from urban transport, Beijing, Guangzhou, Shanghai, and Shenzhen are the top four cities for CO_2 emissions in China, while they rank third, fourth, sixth and twelfth, respectively, in the world. However, in terms of the per capita CO_2 emissions of urban transport, Beijing, Guangzhou, and Shenzhen remain the top three emitters, but Shanghai drops to rank only eighth in

Fig. 1. Geographical distribution of the 180 cities.

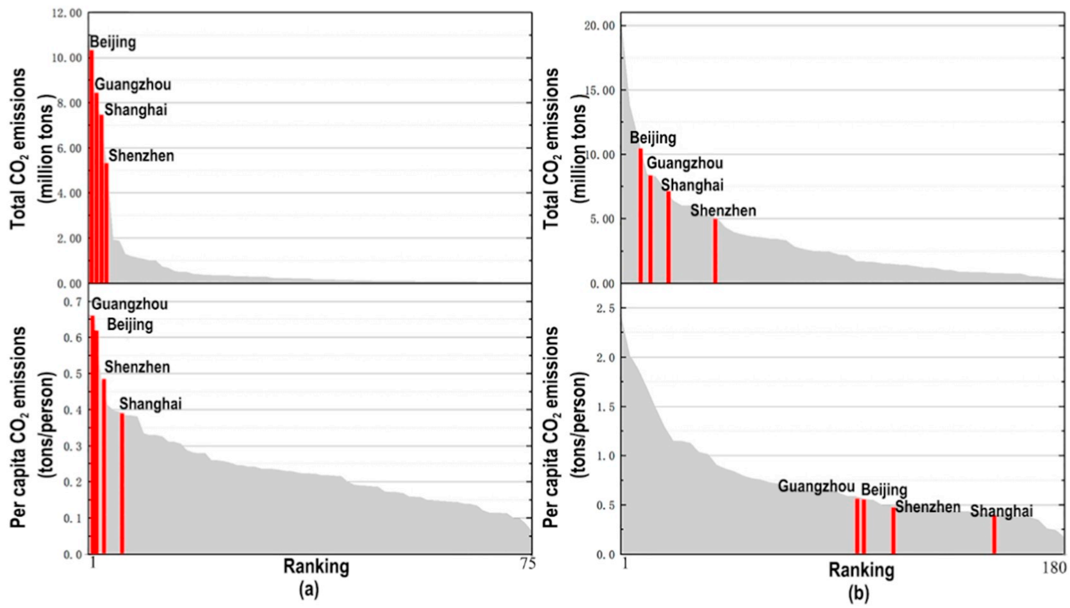

Fig. 2. Ranking of the (a) Chinese cities; (b) global cities.

China. From the global view, these four cities rank behind more than half of the global cities.

To further compare the four cities with other megacities in the world, two European cities (Paris and London), two Asian cities (Tokyo and Seoul) and two North American cities (New York and Chicago) were selected. Table 3 compares the total CO_2 emissions and per capita CO_2 emissions of urban transport in these megacities. In 2012, the total CO_2 emissions of urban transport in Beijing, Shanghai, and Guangzhou were higher than those in Paris, London and Seoul. For the per capita CO_2 emissions, these three Chinese cities remained at the same levels as Paris and London but were higher than Tokyo and Seoul. In addition, the per capita CO_2 emissions of the four Chinese cities have all increased, while those of the other cities have decreased since 1995.

The above analysis is the absolute evaluation of low-carbon urban transport. It shows that the CO_2 emissions of urban transport vary by city and change over time. Although the total CO_2 emissions and per capita CO_2 emissions of the different cities are compared and ranked, decision makers still cannot determine whether the urban transport in those cities is low carbon. In addition, the rank of a city does not reflect the level of low-carbon urban transport. Not only policy measures but also the urban population scale, population density, and economic development factors could have significant effects on urban transport emissions. Consequently, the absolute evaluation cannot reflect whether the cities provide appropriate policies for encouraging low-carbon transport.

Table 3
Comparison of the CO_2 emissions of urban transport in megacities.

City	Total CO_2 emissions (million tons CO_2)		Per capita CO_2 emissions (ton CO_2/per capita)	
	1995	2012	1995	2012
Paris	11.05	5.15	1.00	0.43
London	6.61	5.36	0.94	0.64
New York	43.82	NA	2.60	NA
Chicago	23.45	20.46	3.12	2.42
Tokyo	23.86	13.7	0.74	0.37
Seoul	13.03	6.87	0.63	0.28
Shanghai	1.06	7.32	0.13	0.38
Beijing	1.55	10.64	0.25	0.63
Guangzhou	0.60	8.44	0.15	0.66
Shenzhen	NA	5.04	NA	0.49

4. Comparative evaluation method

As mentioned above, low-carbon urban transport mainly indicates that policy measures are effective for maintaining CO_2 emissions at a relatively lower level. To independently evaluate the effects of policy measures, first, the effects of other factors (i.e., urban population scale, population density and economic factors) are analyzed and eliminated. Then, a comparative evaluation method of low-carbon urban transport that considers the heterogeneity of populations and economies in different cities is proposed.

4.1. Scaling effect analysis

To explore the relationship between the total population and the total CO_2 emissions of urban transport, the corresponding scatter diagrams of the 180 cities on different continents are presented in Fig. 3. The figure shows that the total CO_2 emissions increase with population scale on the same continent. However, the growth rates on different continents and over time are different. The population scales of the Asian cities are mostly larger than those of the Australian, European and North American cities. However, the total CO_2 emissions of urban transport in Asian cities are usually smaller.

Many empirical studies have also indicated that the total CO_2 emissions of transport will accelerate with the growth of the population (Fragkias et al., 2013). The larger the population, the more social interaction will be induced, which leads to more activities and emissions. This phenomenon is called the "urban scaling effect" (Bettencourt, 2013). Previous studies have indicated that superlinearity exists in the relationship between population scale and total CO_2 emissions (Fragkias et al., 2013), which is formulated as

$$C = \alpha_1 \bullet P^{\beta_1} \tag{4}$$

$$ln(C/P) = \ln(\alpha_1) + (\beta_1 - 1)\, ln(P) \tag{5}$$

$$ln(PC) = \alpha_2 + \beta_2\, ln(P) \tag{6}$$

where P is the urban population and α_1, α_2 β_1, and β_2 are the regression coefficients. Given $1 < \beta_1 < 2$ and $0 < \beta_2 = \beta_1 - 1 < 1$, the relationship between population scale and per capita CO_2 emissions of urban transport is sublinear.

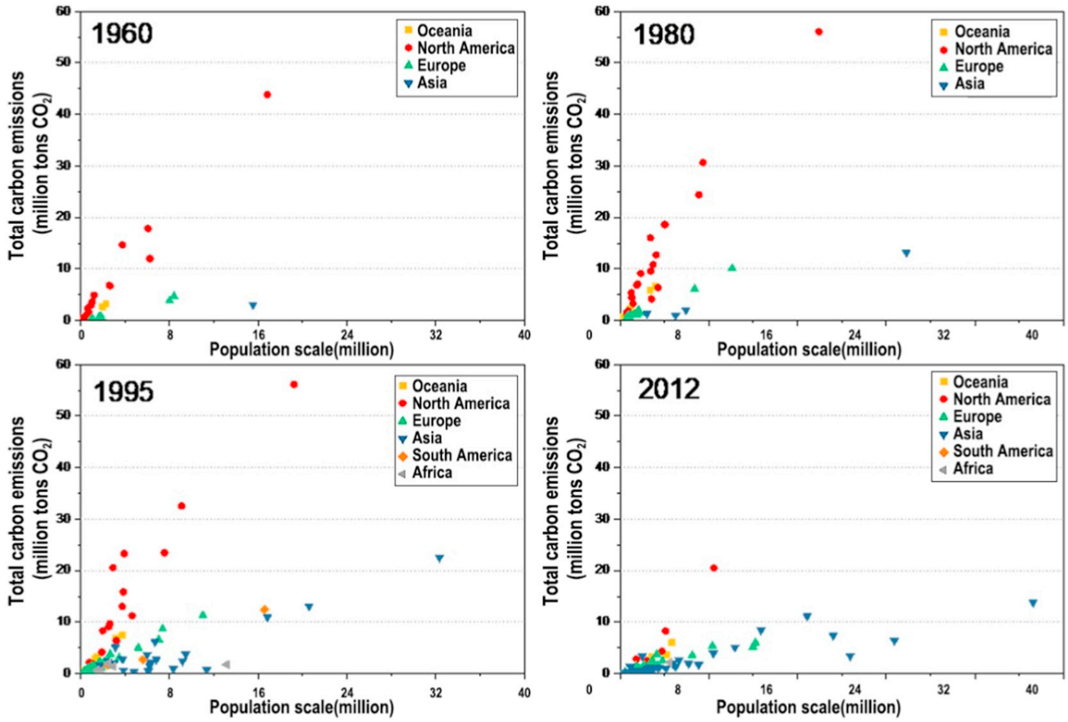

Fig. 3. The relationship between the total CO_2 emissions and the population scale.

4.2. Density effect analysis

To explore the relationship between population density and the per capita CO_2 emissions of urban transport, the corresponding scatter diagrams of the 180 cities on different continents are presented in Fig. 4. The figure shows that the per capita CO_2 emissions decrease with population density in all cities across the different continents. The populations of the Asian cities are generally denser than those of cities on other continents. As a result, the per capita CO_2 emissions of urban transport in Asian cities are usually lower.

Many researchers have proven that there is a negative correlation between population density and CO_2 emissions (Jones and Kammen, 2014; Norman Jonathan et al., 2006). Newman and Kenworthy (1989) found that the lower the population density is, the lower the per capita CO_2 emissions of transport. According to the data from 180 cities in different years, the relationship between population density and the per capita CO_2 emissions of transport is inversely proportional, which is formulated as

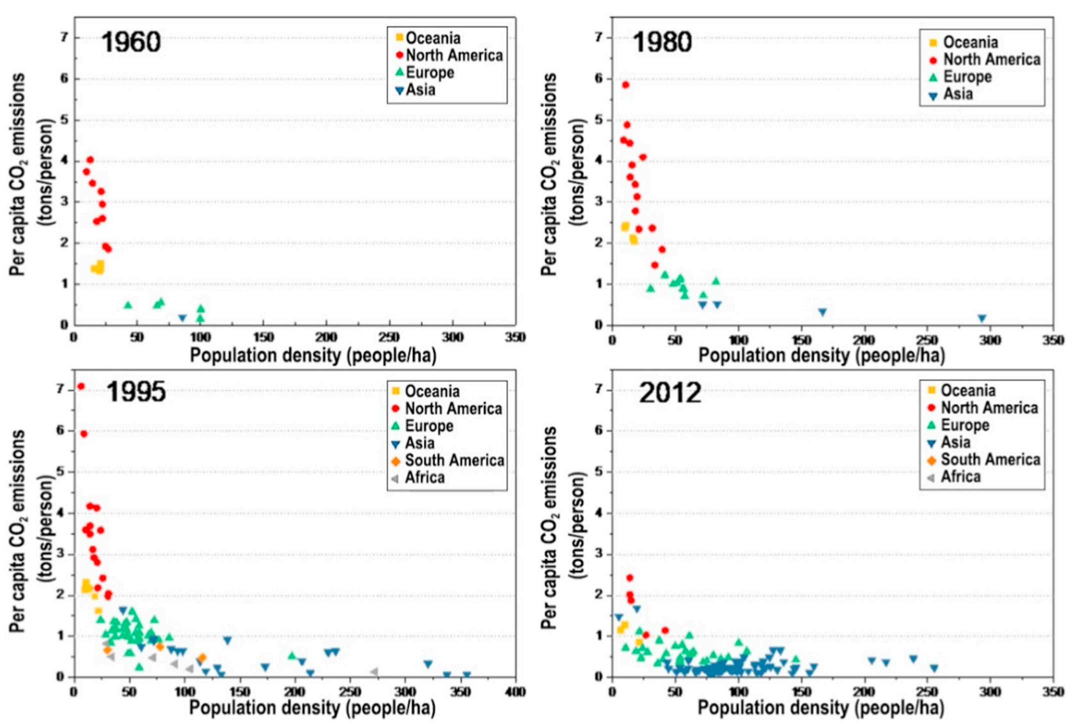

Fig. 4. The relationship between per capita CO_2 emissions and population density.

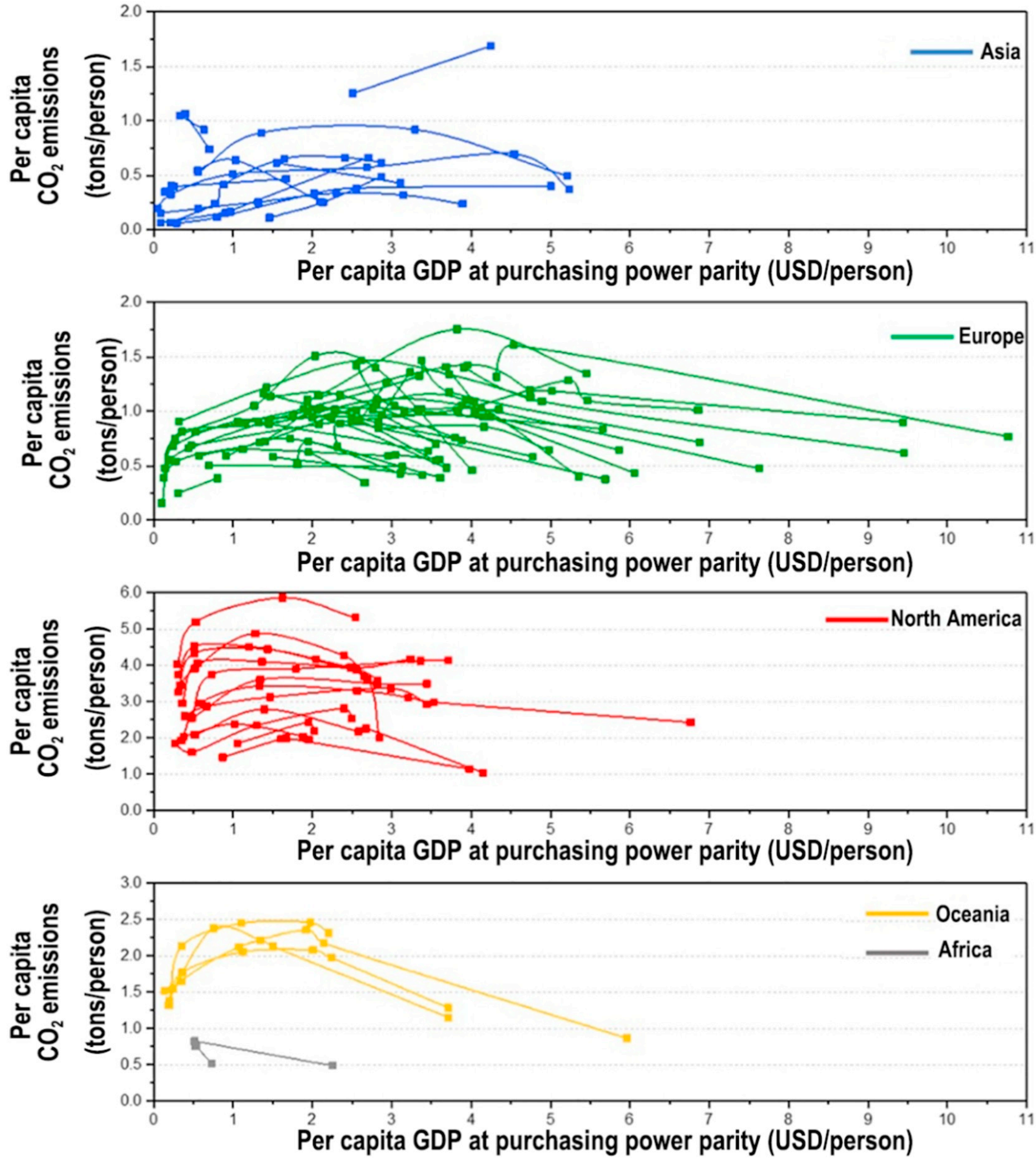

Fig. 5. The relationship between per capita CO_2 emissions and per capita GDP.

$$PC = \alpha_3 \cdot D^{-\gamma_1} \tag{7}$$

$$\ln(PC) = \ln(\alpha_3) - \gamma_1 \cdot \ln(D) \tag{8}$$

where D is the urban population density, and α_3 and γ_1 are the regression coefficients.

4.3. Economic effect analysis

To explore the relationship between per capita GDP and the per capita CO_2 emissions of transport, the corresponding curves of the 180 cities on the different continents are presented in Fig. 5. Each curve represents the transition of a city from 1960 to 2012. The results show that per capita CO_2 emissions will usually reach a peak with the growth of per capita GDP and decrease gradually afterward.

Quantifying the relationship between economic development and the environment is currently a hot area of research (Stern et al., 1996). The most representative method is the environmental Kuznets curve (EKC), which is widely used for studying the relationship between per capita GDP and environmental pollution (Fodha and Zaghdoud, 2010; Jalil and Mahmud, 2009). In general, the EKC is an "inverted U" curve that can be formulated as

$$ln(PC) = \alpha_4 + \delta_1 ln(PGDP) + \delta_2 [ln(PGDP)]^2 \tag{9}$$

where $PGDP$ is the per capita GDP, and α_4, δ_1, and δ_2 are the regression coefficients.

4.4. Benchmark model

Apart from the urban scaling, population density and economic effects analyzed above, there are many other factors that can influence the per capita CO_2 emissions of transport, including energy structure, car ownership, vehicle technology and the planning of public transport systems (Li et al., 2018a); these can be integrated as policy factors. Policy factors should be considered to reflect the low-carbon development level of urban transport. Therefore, it is necessary to eliminate the effects of urban population scale, population density, and economic development before independently evaluating the effect of policy measures for low-carbon urban transport in different global cities.

This study establishes a benchmark model of per capita CO_2 emissions for different cities with different properties based on a nonlinear

regression model with multiple independent variables: the urban population scale, population density, and economic development. Given the relationships presented above, the benchmark model can be formulated as

$$ln(\widehat{PC}) = \alpha + \beta \bullet ln(P) + \gamma \bullet ln(D) + \delta_1 \bullet ln(PGDP) + \delta_2 \bullet [\ln(PGDP)]^2 \quad (10)$$

where $\widehat{PC}$ is the benchmark (predicted) value of the per capita CO_2 emissions of urban transport, P is the urban population, D is the urban population density, $PGDP$ is the per capita GDP, and α, β, γ, δ_1 and δ_2 are the regression coefficients. Most commonly, regression analysis estimates the conditional expectation of the dependent variable given the independent variables (Allison, 1990). In other words, it reflects the average value of the dependent variable when the independent variables are fixed. Therefore, the benchmark value represents the expected (average) level of per capita CO_2 emissions of urban transport given the specific urban population scale, population density, and economic development.

With the calibrated benchmark model, we can calculate the residual (ε), which is the difference between the true value and the benchmark (predicted) value of the per capita CO_2 emissions. The residual can be written as

$$CEI_i = \varepsilon_i = ln(PC_i) - ln(\widehat{PC_i}) \quad (11)$$

where subscript i indicates a particular city, PC_i is the true value of the per capita CO_2 emissions of urban transport in city i, $\widehat{PC_i}$ is the benchmark value of the per capita CO_2 emissions of urban transport given the same urban population scale, population density, and economic development as city i, and ε_i represents the unexpected influence of the policy factor on the low-carbon transport development in city i, except for the independent variables.

Then, we define $CEI_i = \varepsilon_i$ as the comparative evaluation index for low-carbon urban transport, which can reflect the net effects of the policy measures excluding the influence of urban population scale, population density, and economic development. If $CEI_i < 0$, then the actual per capita CO_2 emissions of urban transport in city i is lower than the benchmark, indicating that the policy measures are effective at keeping the transport CO_2 emissions subaverage; otherwise, the actual per capita CO_2 emissions of urban transport in city i is higher than the benchmark, indicating that the policy measures are not sufficient for controlling the CO_2 emissions of urban transport. Therefore, the level of low-carbon urban transport in different cities can be evaluated and compared using this relative index with respect to the benchmark value of the per capita CO_2 emissions.

5. Results and discussion

5.1. Comparative evaluation results

With the data from the 180 global cities prepared above, the coefficients of the regression model were estimated, as shown in Table 4. To take the time dimension into account, the data were divided into 7 groups based on year (1955–1964, 1965–1974, 1975–1984, 1985–1994, 1995–1999, 2000–2004 and after 2005). The group of data after 2005 is set as the reference. The results show that all the independent variables are significantly correlated with the per capita CO_2 emissions of urban transport. The variance inflation factors (VIFs), the ratio of variance in a model with multiple terms, are all smaller than 2.5, which indicates that the regression model does not have a significant multicollinearity problem (Mansfield and Helms, 1982). In addition, the coefficient of determination, R^2, is equal to 0.838, which indicates that the urban population scale, population density, and economic development factors can explain 83.8% of the variation in the per capita CO_2 emissions of urban transport. Then, the remaining variation should be determined by the policy factor, which also reflects the level of low-carbon urban transport.

Given the calibrated benchmark model, we calculated the benchmark value of the per capita CO_2 emissions of urban transport for each city. Then, the comparative evaluation index (*CEI*) for low-carbon urban transport was finally obtained. The evaluation results of some megacities are presented in Table 5, which illustrates a conclusion different from that in Table 3 above.

When directly comparing the absolute values of the per capita CO_2 emissions among these cities (as shown in Table 3), we conclude that Seoul had the best and Chicago had the worst low-carbon urban transport in 2012. When comparing the *CEI*, the best city was Tokyo, and the worst city was Guangzhou in 2012. Ample evidence shows that Tokyo is recognized as among the global cities that have succeeded in developing low-carbon urban transport (Gomi et al., 2010). For example, Dhakal et al. (2002) estimated and analyzed the CO_2 emissions from energy use in Tokyo and Seoul and analyzed the performance of cities in East Asia. Their results suggest that the performance of Tokyo is outstanding in comparison to other major Japanese cities, Seoul, Beijing, Shanghai, major OECD countries and major non-OECD countries. This finding is consistent with our results. Therefore, the comparative evaluation results may be more reliable than an evaluation based on absolute values.

5.2. Low-carbon urban transport identification

Considering the above definition of *CEI*, the lower the *CEI* is, the higher the level of low-carbon urban transport. If the $CEI_i < 0$, then the urban transport in city i is identified as having low-carbon urban transport. Therefore, the *CEI* is a quantitative standard for determining whether urban transport is low carbon. We ranked all cities based on their *CEI* from large to small, as shown in Fig. 6. The x axis represents the rank of the city, while the y axis represents the value of the *CEI* (e.g., "1st" represents the city with the largest *CEI*). This allows the level of low-carbon urban transport to be easily compared according to the ranks of the cities.

Fig. 6 also lists the top 5 cities in terms of low-carbon and high-carbon urban transport for each year. Blue represents low carbon, while red represents high carbon. For example, Tehran, Rome, Strasbourg, Taipei, and Guangzhou are the top 5 cities in terms of high-carbon urban transport in 2012. This may result from the high proportion of auto travel in these cities. In the same year, Tokyo, Gothenburg, Paris, Copenhagen and Lisbon are the top 5 cities for low-carbon urban transport, which is consistent with their public reputation (Mega, 2010; Mingardo, 2008).

To verify the evaluation results, some results from previous related studies are discussed. For example, Azizalrahman and Hasyimi (2018a, b) concluded that Sydney, London, Copenhagen, Stockholm, São Paulo, Bogota and Vancouver were low-carbon cities based on a multicriteria evaluation model. Their results and our results are similar but slightly different because their evaluation is for low-carbon cities rather than low-carbon urban transport. In their study, urban transport only accounted for 19% of the evaluation of the low-carbon cities (Azizalrahman and Hasyimi, 2018a). In addition, their study only identified 7 low-carbon cities from the 15 selected global cities (Azizalrahman and Hasyimi, 2018b). Our study evaluated the low-carbon urban transport of 180 global cities. To the best of our knowledge, none of the previous studies have evaluated and compared the level of low-carbon urban transport among so many global cities. Therefore, our results are meaningful and unique.

5.3. Low-carbon urban transport transition

Based on the comparative evaluation indexes in different years, we identified the transition of urban transport for each city. The transitions are classified into four types: stable high-carbon, stable low-carbon, low-carbon transitions, and high-carbon transitions. Fig. 7 presents

Table 4
Estimated coefficients of the benchmark model.

Independent variable		Unstandardized coefficients	Standardized coefficients	T	Sig.	95.0% confidence interval		Colinear statistics	
		B	Beta			Lower limit	Upper limit	Tolerance	VIF
(Intercept)		0.856		5.106	***	0.526	1.186		
ln (P)		0.123	0.138	6.199	***	0.084	0.163	0.878	1.139
ln (D)		−0.663	−0.543	−20.218	***	−0.728	−0.599	0.606	1.650
ln(PGDP)		0.392	0.392	12.382	***	0.330	0.454	0.436	2.294
$[\ln(PGDP)]^2$		−0.063	−0.083	−3.718	***	−0.096	−0.030	0.868	1.152
Year	1955–1964	1.716	0.369	12.115	***	1.438	1.995	0.470	2.128
	1965–1974	1.586	0.395	13.561	***	1.356	1.816	0.514	1.945
	1975–1984	1.181	0.328	12.580	***	0.996	1.365	0.642	1.558
	1985–1994	1.061	0.314	12.754	***	0.897	1.224	0.721	1.387
	1995–1999	0.935	0.382	14.565	***	0.809	1.061	0.635	1.575
	2000–2004	0.614	0.203	8.707	***	0.475	0.753	0.804	1.244

Note: Sig. codes: p-value = 0 '***', 0.001 '**', 0.01 '*', 0.05 '.', 0.1 ' ', and 1; Adjusted R-squared: 0.838.

Table 5
Comparative evaluation indexes of megacities.

Global city	CEI	
	1995	2012
Paris	−0.49	−0.63
London	−0.23	0.02
New York	−0.12	NA
Chicago	0.03	0.42
Tokyo	−0.63	−0.84
Seoul	0.43	−0.22
Shanghai	−1.15	0.51
Beijing	−0.68	0.74
Guangzhou	−1.18	0.77
Shenzhen	NA	0.43

some typical cities for each type of transitions. For example, Phoenix, Montreal, and Manila failed to take effective measures to control urban transport emissions, and thus, they are classed as the stable high-carbon type. Paris, Tokyo, and Copenhagen maintained a low level of CO_2 emissions, and thus, they are classified as stable low-carbon type. Shanghai and Beijing experienced dramatic increases in their *CEIs* during recent decades, and therefore, they are classed as the high-carbon transition type. Seoul is typical of the low-carbon transition type because its *CEI* continued to decrease from 1990 to 2012. It is necessary for cities of stable high-carbon-type and high-carbon transition-type to learn from the experiences, technologies, and management abilities of stable low-carbon and low-carbon transition cities.

Taking Tokyo and Shanghai for comparison, both Tokyo and Shanghai have experienced rapid growth in terms of population, the economy, and urbanization during recent decades. However, Tokyo maintains a stable low-carbon status, while Shanghai has transitioned toward a high-carbon status. This is consistent with the results of a previous study (Luo et al., 2017a) and can be explained by the different low-carbon development policies of these two cities. In Tokyo, successful transit-oriented development (TOD), strict car-parking policies, high usage fees for cars and the high service level of railways significantly decreased the use rate of private cars, and therefore, the per capita CO_2 emissions were relatively low. Rapid urban expansion in Shanghai led to an increase in travel distance, car ownership and a mode shift to private cars (Li et al., 2010). In addition, the low level of public transport services and lack of strong controls on car usage further increased the use of private cars. Although some policy measures were taken to increase the fuel efficiency of vehicles, the effect was quite limited. Therefore, Shanghai still needs to learn from the successful experience of Tokyo for its low-carbon urban transport transition, such as TOD, car-usage control and low-carbon technology promotion.

6. Conclusions and policy implications

To address the lack of a comparable and comprehensive evaluation of low-carbon urban transport, a comparative evaluation method considering the effects of urban population scale, population density and economic development was developed. First, the CO_2 emissions of urban transport in 180 global cities were measured through top-down and bottom-up approaches. Second, the absolute rankings of these cities in terms of urban transport CO_2 emissions were obtained based on the measurement of CO_2 emissions. However, this ranking cannot represent the level of low-carbon urban transport, since it ignores the effects of urban heterogeneity. Thus, the effect of urban population density, urban scaling, and the urban economy were analyzed to build a benchmark model for the evaluation of global low-carbon urban transport. Then, a comparative evaluation index was derived from the benchmark model to independently evaluate the effects of policy factors, which may reflect the level of low-carbon urban transport. As a result, cities with low-carbon urban transport were identified. Furthermore, four types of urban transport transitions were identified: stable high-carbon transitions, stable low-carbon transitions, low-carbon transitions, and high-carbon transitions. The major findings of this study are summarized as follows:

- Four Chinese megacities, Beijing, Shanghai, Guangzhou, and Shenzhen, rank ahead of most global cities in terms of total CO_2 emissions, while they rank behind more than half of the global cities in terms of per capita CO_2 emissions;
- The relationship between the population scale and the per capita CO_2 emissions of urban transport is sublinear, the relationship between population density and the per capita CO_2 emissions of urban transport is inversely proportional, and the relationship between the per capita GDP and the per capita CO_2 emissions of urban transport could be fitted with the Kuznets curve;
- Tokyo, Gothenburg, Paris, Copenhagen and Lisbon are the top 5 cities in terms of low-carbon urban transport in 2012, while Tehran, Rome, Strasbourg, Taipei, and Guangzhou are the top 5 cities in terms of high-carbon urban transport in 2012;
- Urban transport in Phoenix, Montreal, and Manila is of the stable high-carbon type; that in Paris, Tokyo, and Copenhagen is of the stable low-carbon type; that in Shanghai and Beijing is of the high-carbon-transition type; and Seoul is a typical city of a low-carbon transition that should serve as an example for other cities.

The benchmark model and the comparative evaluation index proposed in this study are practical and applicable and can provide policy makers with a better view of the low-carbon development level of urban

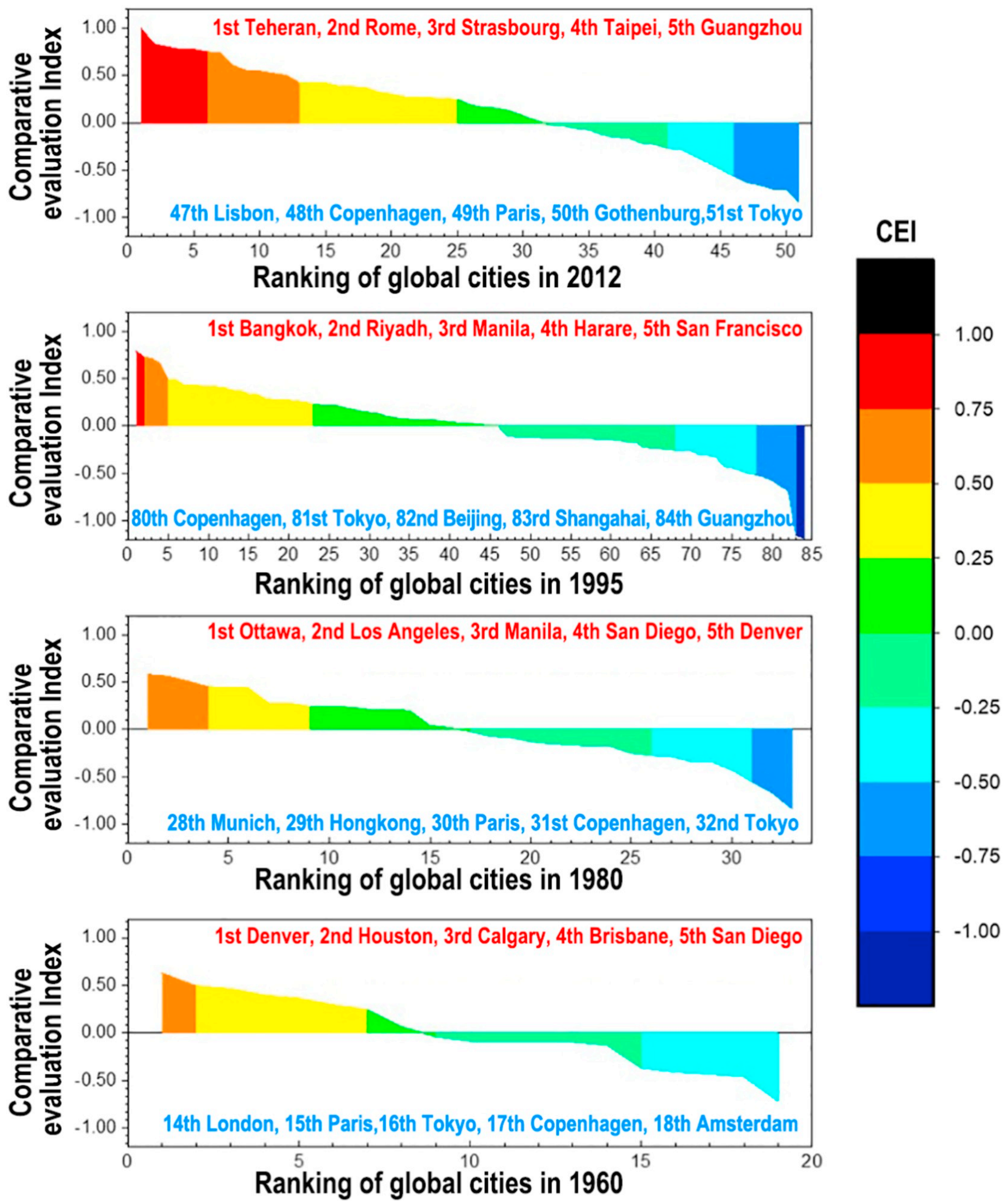

Fig. 6. Rankings of global cities based on the comparative evaluation index.

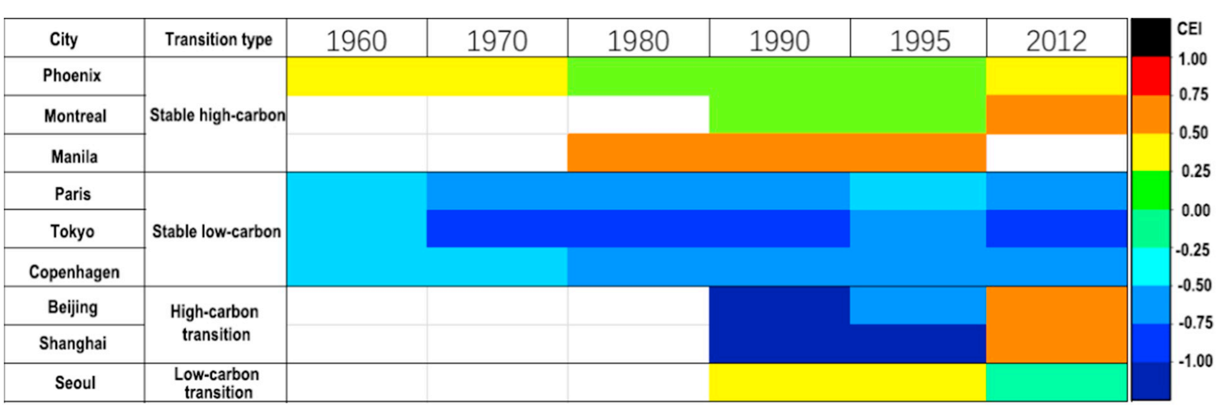

Fig. 7. The transition of urban transport.

transport. Given the per capita CO_2 emissions of urban transport, urban population scale, population density and per capita GDP of a city, a government can easily use our calibrated regression model to calculate the benchmark for a given city. If the per capita CO_2 emissions of urban transport are higher than the benchmark, then the policy measures in that city are not sufficient for keeping the CO_2 emissions of urban transport at a relatively low level. Therefore, the government should propose more effective strategies and instruments to support low-carbon urban transport development. Some available options include transit-oriented development, low-emission vehicle development, emission standards, road pricing, and CO_2 emission trading. If the per capita CO_2 emissions of urban transport are lower than the benchmark, then the city has low-carbon urban transport. The difference between the true value of the per capita CO_2 emissions and the benchmark is used as a comparative evaluation index, which is useful for cities to see where they are ranked in terms of global low-carbon urban transport. This metric can help a city better learn from the successful experiences of top-ranking cities with low-carbon urban transport. In addition, the comparative evaluation index also provides a reference for the progress of low-carbon urban transport transitions. In summary, the comparative evaluation index is necessary to policy makers for evaluating and improving the low-carbon development level of urban transport in a city.

There are some limitations to the current study, which can also motivate a few future research directions. First, the object of this research was urban passenger transport, and urban freight transport was excluded due to a lack of related data. In fact, freight transport also contributes significantly to the CO_2 emissions of cities. The effects of population scale, population density and economic development on freight emissions should be further investigated in future work with more available data. Second, the comparative evaluation was based only on the per capita CO_2 emissions of urban transport. However, the CO_2 emissions per GDP could be another evaluation indicator and will be integrated in a follow-up study. Finally, the benchmark model mainly considers the effects of urban population scale, population density and economic development. Including some other nonpolicy-related factors, such as geographic features, construction land area, and urbanization rate of a city, could further improve the accuracy of the comparative evaluation.

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Appendix A

Table A
1 full list of global cities.

Area		City					
Asia	China	Beijing	Shanghai	Guangzhou	Shenzhen	Taipei	Hong Kong
		Tianjin	Harbin	Shenyang	Hangzhou	Xi'an	Wenzhou
		Jinan	Taiyuan	Xiamen	Changsha	Qingdao	Zhengzhou
		Xuzhou	Kunming	Zhongshan	Liuzhou	Xining	Lanzhou
		Laiwu	Taian	Baotou	Weifang	Zhuhai	Baoji
		Tin shui	Jining	Fuzhou	Wuhu	Shijiazhuang	Baoding
		Wuwei	Bengbu	Luzhou	Yibin	Binzhou	Pingliang
		Lianyungang	Linfen	Sanya	Liaoyang	Weihai	Anqing
		Zhuzhou	Anshun	Bayan nur	Maanshan	Weinan	Korla
		Xuancheng	Tongliao	Puyang	Chengde	Xintai	Qufu
		Dafeng	Yan'an	Qingzhou	Duyun	Liupanshui	Nanping
		Zhongwei	Qingzhen	Carey	Tongren	Ordos	Jishou
		Tianchang	Yangzhong	Shaowu			
	Middle East	Dubai	Abu Dhabi	Jerusalem	Tel Aviv	Riyadh	Tehran
	Other	Manila	Seoul	Kuala Lumpur	Osaka	Sapporo	Tokyo
		Bangkok	Singapore	Mumbai	Chennai	Surabaya	Jakarta
		Ho Chi Minh City					
Europe		Munich	Dusseldorf	Ruhr	Hamburger	Stuttgart	Moscow
		Leon	Frankfurt	Marseilles	Nantes	Paris	Lille
		Clermont-Ferrand	Strasbourg	Helsinki	Amsterdam	Rotterdam	Prague
		Oslo	Lisbon	Stockholm	Fort Gothic	Zurich	Geneva
		Berne	Barcelona	Madrid	Bilbao	Seville	Valencia
		Athens	Budapest	Rome	Turin	Milan	Bologna
		Birmingham	Manchester	Newcastle	Glasgow	London	Vienna
		Graz	Brussels	Ghent	Warsaw	Krakow	Copenhagen
		Berlin					
North America		Vancouver	Toronto	Ottawa	Calgary	Winnipeg	Edmonton
		Montreal	Sacramento	San Diego	Phoenix	Detroit	Boston
		Atlanta	Houston	Los Angeles	Denver	New York	Washington
		Chicago	Portland	San Francisco			
Oceania		Canberra	Melbourne	Sydney	Adelaide	Perth	Brisbane
		Wellington					
South America		Curitiba	São Paulo	Bogota			
Africa		Cairo	Tunisia	Harare	Johannesburg	Cape town	Dakar

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Wenxiang Li is currently a Ph.D. candidate at the College of Transportation Engineering, Tongji University, China. He was a visiting student at Department of Civil and Environment Engineering, University of Washington from September 2017 to September 2018. His research focuses on sustainable transportation, which includes carbon emission trading of transport sector, low-carbon transport evaluation, planning of electric vehicles and shared mobility. He also has a great interest in the mining and analytics of big data, such as the applications of mobile phone data, location-based service (LBS) data and GPS data. During the recent five years, he has published over 10 papers in international journals such as Transportation Research Part C: Emerging Technologies, Sustainability, Transportation Research Record, Transport Policy, etc.

Lei Bao is an engineer at the Seazen Holdings Co., Ltd. He received his Ph.D. degree in the College of Transportation Engineering, Tongji University, China. He was a visiting scholar at Lawrence Berkeley National Laboratory from March 2016 to September 2016. His research focuses on energy and environment analysis of transportation, which includes transport emission prediction, low-carbon transport evaluation, and emissions mitigation policy.

Luqi Wang is a Ph.D. candidate at the School of Management, Harbin Institute of Technology. She was a visiting scholar at Department of Civil and Environment Engineering, University of Washington from October 2017 to October 2018. Her research focuses on transport de-carbonization, transport project management and mega project management. Inspired by the existing research hotpots at the machine learning, her research emphasized the differences between parameter methods and non-parameter methods at the transport emission analysis. She has reviewed and published some articles related to spillover effect of transport infrastructures, transport emission prediction and transport project management in several peer-reviewed academic journals.

Ye Li is a professor at the College of Transportation Engineering, Tongji University, China. He has made a long-term commitment to the teaching and research work of comprehensive transportation system planning. During the past few years, he has been engaged in frontier research of low carbon transportation system planning, transportation service pattern innovation with Big Data. He has hosted over 20 research subjects such as National Natural Science Foundation Project, Soft Science Project of Ministry of Transport, the Joint Specialized Research Fund for the Doctoral Program of Higher Education Project, Shanghai Philosophy and Social Science Fund Project, Key Subject of Academic Degree Commission of the State Council. He has obtained significant achievement in areas of regional transportation planning, low carbon transportation planning, slow traffic planning.

Xianmin Mai is a professor and the vice dean at the School of Urban Planning and Architecture, Southwest Minzu University, China. She was a JSPS Researcher at Nagoya University from April 2009 to March 2011. She received her Ph.D. degree in the College of Architecture and Urban Planning, Tsinghua University, China. Her research focuses on sustainable development of regional cities, quality of life evaluation, and low-carbon urban transport development.